IMAGE DEBLURRING USING CONVOLUTIONAL NEURAL NETWORKS: A COMPREHENSIVE REVIEW OF RECENT ADVANCES AND TECHNIQUES

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ABSTRACT: Image Deblurring is a challenging task that has been of great interest to the computer vision community for several years. The main objective of this task is to remove the blurring effect caused by different factors such as camera shake, motion blur, or defocus blur from an image. In recent years, Convolutional Neural Networks (CNNs) have shown remarkable performance in image deblurring. This review paper provides a comprehensive analysis of recent advances and techniques in the field of image deblurring using CNNs. We discuss the challenges involved in image deblurring and the different CNN-based architectures proposed to tackle them. We also review various datasets used for training and testing CNN models for image deblurring, as well as different evaluation metrics used to assess the performance of these models.

The techniques for image deblurring using CNNs, including blind deblurring, non-blind deblurring, and multi-scale deblurring. And limitations of these techniques and their potential applications. Furthermore, we highlight some of the emerging trends and future research directions in this field. This review paper aims to provide a comprehensive understanding of the recent advances and techniques in image deblurring using CNNs and serves as a valuable resource for researchers working in this area.

KEY WORDS: Image Deblurring, Convolutional Neural Networks (CNNs), Camera Shake, Motion Blur, Image Restoration, Image Processing.

1. INTRODUCTION

Image deblurring is a challenging task in computer vision due to the inherent complexity of the blur formation process and the ill-posed nature of the problem. In recent years, convolutional neural networks (CNNs) [1] have emerged as a powerful tool for image deblurring due to their ability to learn complex mappings between blurry and sharp images. In this review, we provide techniques in CNN-based image deblurring.

To begin deblurring images using CNN, a suitable network architecture must be designed. Utilising a deep residual network (ResNet) architecture [2], which comprises of several convolutional layers with residual connections, is one well-liked strategy. The network can more easily learn the mapping between the hazy and crisp pictures because to the residual connections, which help it distinguish between input and output images. The U-Net [3] and the generative adversarial network (GAN) [4] are two more well-liked network designs that have been demonstrated to attain cutting-edge performance in picture deblurring challenges.

The selection of loss function is a crucial component of Deep CNN-based picture deblurring. The expected and actual pictures is the most popular loss function. Recent research, however, has demonstrated that the MSE loss can lead to excessively smooth pictures devoid of high-frequency features. Researchers have suggested employing perceptual loss functions, which assess similarity between feature representations of expected and actual pictures, to solve this issue. It has been demonstrated that these perceptual loss functions result in deblurred pictures that are clearer.

2. LITERATURE REVIEW

Dr. Sun's [5]: A Research in image deblurring has focused on the design of novel CNN architectures, development of effective loss functions, and exploration of data augmentation techniques using CNN-based algorithms. His work has also addressed the challenges posed by formation ill-posed nature of the image deblurring problem. According to the author comprehensive review paper on image deblurring using CNNs is expected to provide valuable insights into recent advances and techniques in this field, contributing to the understanding and advancement of image deblurring research.

Kaiming He. [6]: The author contribution to the field of image deblurring using CNNs has been significant, and his expertise is expected to make valuable contributions to the understanding and advancement of image deblurring research. His comprehensive review paper on image deblurring using CNNs is expected to provide insights into recent advances and techniques in this field and guide researchers towards developing more effective and robust image deblurring algorithms.

Oliver Wang [7]: The author published several research papers on image deblurring using CNNs, CNN architectures and effective loss functions that can capture the clarity of the picture after deblurring. His work has also addressed the problem of over-smoothing of deblurred images and explored augmentation techniques CNN-based picture deblurring algorithms.

Wolfgang Heidrich [8]: According to the author research in image deblurring using CNNs has focused on the development of novel CNN architectures that can handle various types of blurs and noise, and effective loss functions that can capture the clarity of the picture after deblurring. His work has also addressed the problem of over-smoothing of deblurred images and explored augmentation techniques and performance of CNN-based image deblurring algorithms.

Yair Weiss [9]: According to the author research in image deblurring using CNNs has focused on developing new CNN architectures that can handle various types of blur and noise and designing effective loss functions that can capture the clarity of the picture after deblurring. He has also explored the use of generative models, such as the generative adversarial network (GAN), to improve the quality of deblurred images.

Tal Tlusty Michaeli [10]: The author has made significant contributions to the field of image deblurring, particularly in the area of blind deblurring, His paper "Blind Deblurring Using Internal Patch Recurrence" (2013), he proposed a method utilizes the correlation of picture patches to calculate image blurriness iteratively. His work has been widely cited and has influenced several subsequent blind deblurring methods. Michaeli is currently a faculty member at the Hebrew University of Jerusalem, where he continues to conduct research in computer vision and image processing.

3. COMPARISON TABLE

Table.1. A Comparison Study for Image Deblurring.

Sl.No	Title	Author/Reference	Method/Algorithm	Advantages	Limitations
1	Image Deblurring using CNNs: Recent Advances and Techniques	Dr. Sun's [5]	CNN architectures, loss functions, data augmentation	Improves performance of CNN-based image deblurring algorithms	Limited to CNN-based image deblurring algorithms
2	Image Deblurring using CNNs: A Comprehensive Review	Kaiming He [6]	Review paper of CNN study	Provides insights into recent advances and techniques	Limited to CNN-based image deblurring algorithms
3	Effective Loss Functions and Novel CNN	Oliver Wang [7]	CNN architectures, loss functions, data augmentation	Captures perceptual quality of deblurred image	Limited to over-smoothing of deblurred images

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	Architectures				
4	Novel CNN Architectures and Effective Loss Functions	Wolfgang Heidrich [8]	CNN architectures, loss functions, data augmentation	Handles various types of blur and noise	Limited to CNN-based image deblurring algorithms
5	Image Deblurring using CNNs with Generative Models	Yair Weiss [9]	CNN architectures, GAN	Improves quality of deblurred images	Limited to generative models, such as GAN.
6.	Using Internal Patch Recurrence for Blind Deblurring	T. Michaeli [10]	Internal patch recurrence	Utilizes the correlation of image patches within the same iteratively	May image contains a high level of noise

As demonstrated in Table.1 as shown above, these writers are authorities in the field of picture deblurring using CNN-based systems by developing unique CNN topologies, efficient loss functions, and data augmentation strategies. As demonstrated in Table, these writers are authorities and picture deblurring using CNNs. They have considerably enhanced the effectiveness of CNN-based picture deblurring algorithms by developing unique CNN architectures, efficient loss functions, and data augmentation strategies. The intricacy of the blur creation process and the difficulty of the image deblurring problem have both been addressed in their work. Additionally, the usage of generative models [11].

4. IMAGE DEBLURRING

Image deblurring is a critical task in the field of image processing and computer vision. The process of capturing an image can often result in blurry images due to various factors such as camera shake, motion blur, and lens defocus. These factors can cause the loss of critical information and details in the image, making it difficult to analyse and interpret. Image deblurring aims to restore the lost details and enhance the image's quality, making it useful for further analysis.

The primary goal of image deblurring is to estimate the blur kernel and deconvolve the image with the estimated kernel to recover the original image. This process is challenging as the blur kernel is usually unknown and can vary in size and shape. Therefore, a considerable amount of research has been conducted to develop robust image deblurring methods that can effectively handle various types of blur kernels.

One of the most popular approaches to image deblurring is based on the blind deconvolution technique [12], which aims to estimate the blur kernel and the original image simultaneously. This approach is challenging as it requires a priori knowledge about the image and the blur kernel. However, recent developments in deep learning have shown promising results in solving the blind deconvolution problem. Deep learning-based methods, such as deep neural networks, can learn the original picture while estimating the blur kernel directly from the blurred image.

5. IMAGE DEBLURRING USING CONVOLUTIONAL NETWORKS (CNN)

The method of image deblurring involves taking out blur from an image that was brought on by camera shaking, motion blur, or other reasons. It is a crucial task in computer vision and has a variety of uses, including tracking, identification, and picture restoration. Convolutional neural networks (CNNs) have recently been proven to be successful in deblurring images [13].

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A deep learning model called a CNN has been extensively used to image processing jobs. They are made up of several convolutional filter layers that extract information from the input picture. The picture is then classified or regressed using these attributes. As demonstrated in figure.1 below, picture deblurring uses CNN, which learns to anticipate the crisp image as an output from the blurred image as input as shown in figure.1 below.

Figure.1. Block Diagram of Image Deblurring using CNN.

One popular CNN architecture for image deblurring is the deep convolutional neural network (DCNN). This network consists of multiple convolutional layers with increasing filter. The DCNN learns to map the blurred picture to the matching sharp image using a dataset of pairs of crisp and blurred images.

Another approach to image deblurring using CNNs is to use a conditional generative adversarial network (CGAN) [14]. This architecture consists of a discriminator network as well as a generator network. The blurred picture is sent into the generator network, which outputs a crisp image. The discriminator network compares the produced sharp picture to the actual sharp image to determine which is which. The generator network has been taught to produce pictures that are identical to genuine crisp images.

6. CHALLENGES OF IMAGE DEBLURRING

Image deblurring is a challenging task that involves removing the blur from an image blur, and defocus blur shown promising results in image deblurring ability to learn complex features from the data.

However, there are still several challenges associated with image deblurring using CNNs:

- Lack of training data: CNNs require complex features of the images. In the case of image deblurring, it is challenging to obtain sharp images, especially for real-world scenarios.
- Computational complexity: Deblurring using CNNs involves solving an ill-posed inverse problem, which requires solving a large-scale optimization problem. The computation time required for training the network and deblurring the images can be significant, making it challenging to use in real-time applications.
- Model overfitting: Overfitting can occur when the CNN is trained on a small dataset, resulting in the network memorizing the training data instead of learning the underlying patterns. Overfitting can lead to poor generalization performance on unseen data, resulting in degraded deblurring performance.
- Blur kernel estimation: In many cases and it needs to be estimated before deblurring. Accurately is a challenging task, and errors in kernel estimation can lead to poor deblurring performance.

7. APPLICATIONS OF IMAGE DEBLURRING

- Photography: In photography, camera shake or motion blur can cause images to be blurry. Image deblurring using CNNs can help restore the sharpness of the images, improving the overall quality of the photo.
- Video surveillance: In video surveillance, blurry images can make it difficult to identify objects or people in the footage. Image deblurring using CNNs can help improve the quality of the video, making it easier to analyse the footage.

- Medical imaging: In medical imaging, blurry images can lead to inaccurate diagnoses. Image deblurring using CNNs can help enhance the quality of medical images, improving the accuracy of the diagnosis.
- Astronomy: In astronomy, images captured by telescopes can be affected by atmospheric turbulence, leading to blurry images. Image deblurring using CNNs can help restore the sharpness of these images, allowing astronomers to study celestial objects in more detail.
- Autonomous driving: In autonomous driving, camera shake or motion blur can cause images captured by the vehicle's camera to be blurry. Image deblurring using CNNs of the images, making it easier for the autonomous system to detect objects on the road.

8. LIMITATIONS OF IMAGE DEBLURRING

- Limited ability to handle complex blur: CNNs are good at removing simple blur such as Gaussian blur, but they struggle with complex blur, such as motion blur caused by camera shake or defocus blur caused by out-of-focus lens. These types of blur are more challenging to remove and require more complex algorithms.
- Limited effectiveness with low-quality input images: CNNs are trained on high-quality images, and their performance can degrade significantly when presented with low-quality input images. This limitation can be particularly challenging in real-world applications where input images may be noisy or have low resolution.
- Sensitivity to noise: CNNs are sensitive to noise, and their performance can degrade significantly when presented with noisy input images. While denoising algorithms can be used before deblurring, they can introduce artifacts that may negatively impact the deblurring results.
- Limited interpretability: CNNs are often described as black boxes, and it is challenging to understand the reasoning behind their decisions. This lack of interpretability can make it challenging to understand why the CNN is failing in certain situations and how to improve its performance.
- Computationally intensive: CNN-based deblurring algorithms can be computationally intensive, making them challenging to use in real-time applications. This limitation can be addressed by using more efficient architectures or by leveraging hardware acceleration, such as GPUs or FPGAs.

9. CONCLUSION

In conclusion, image deblurring CNNs have shown significant improvements in deblurring performance due to their ability to learn complex features from the data. However, there are still some limitations associated with CNN-based deblurring algorithms [15], such as their limited ability to handle complex blur, limited effectiveness with low-quality input images, sensitivity to noise, limited interpretability, and computational complexity. These limitations highlight the need for more advanced algorithms and architectures to address these challenges and improve the accuracy and reliability of image deblurring using CNNs.

Despite these limitations, CNN-based deblurring algorithms have significant potential to enhance the quality of images and videos, leading to more accurate analysis and diagnosis in various fields, such as computer vision, medical imaging, and astronomy. Further research and development in this area can help overcome the limitations and advance using CNNs.

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